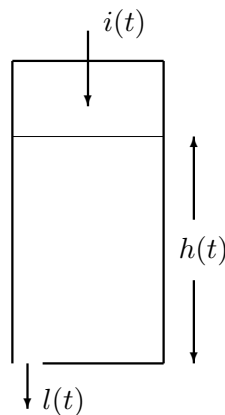


## Integrate and fire

These notes are about a simple but very useful model of spiking neurons: the integrate and fire model. First, though, we consider the dynamics of a leaky bucket of water, in turns out these dynamics are very similar to those seen in the integrate and fire model.

### Buckets of water

In the simplest model of neurons their voltage dynamics is similar to the dynamics of a bucket with a leak and the class of equations that apply in this case will also be applied to synapses, for example.



Consider a bucket with straight sides which is filled to a height  $h$  with water. Imagine the water leaks out of a hole in the bottom. The rate the water leaks out depends on  $h$ ; the larger  $h$  is the larger the pressure at the bottom is and hence the faster the water pours out. In other words

$$l(t) \propto h(t) \quad (1)$$

or

$$l(t) = Gh(t) \quad (2)$$

where  $G$  is a constant which will depend on the size of the hole and complicated things like the viscosity of water. Of course, we are also ignoring lots of complicated stuff, like turbulence and so forth, but since we are interested in the equation rather than the amount of water in a bucket, this is fine. Imagine water also pours in the top at a rate  $i(t)$ . This means the total rate of change of the amount of water is  $i(t) - Gh(t)$ .

Now,  $h(t)$  is the height of the water not the volume: the volume is  $Ch(t)$  where  $C$  is the cross-sectional area of the bucket. The rate of change of the volume is therefore

$$\frac{dCh(t)}{dt} = i(t) - Gh(t) \quad (3)$$

or

$$\frac{dh}{dt} = \frac{1}{C}(i - Gh) \quad (4)$$

This is an equation we know how to solve; we saw it at the start of the course when learning about differential equations. This same equation will appear when we look at the dynamics of a neuron and for similar reasons, something, water in the case of the bucket, charge in the case of a neuron, is being added to a leaky container.

## Electrical properties of a neuron

The potential inside a neuron is lower than the potential on the outside; this difference is created by ion pumps, small molecular machines that use energy to pump ions across the membrane separating the inside and outside of the cell. One typical ion pump is Na<sup>+</sup>/K<sup>+</sup>-ATPase (Sodium-potassium adenosine triphosphatase); this uses energy in the form of ATP, the energy carrying molecule in the body, and through each cycle it moves three sodium ions out of the cell and two potassium ions into the cell. Since both sodium and potassium ions have a charge of plus one, this leads to a net loss of one atomic charge to the inside of the cell lowering its potential. It also creates an excess of sodium outside the cell and an excess of potassium inside it. We will return to these chemical imbalances later. The potential difference across the membrane is called the **membrane potential**. At rest a typical value of the membrane potential is  $E_L = -70\text{mV}$ . It is useful to remember that the excessive sodium is outside the cell and potassium inside; I think of islands which are surrounded by salty water, as in Fig. 1.

## Spikes

So the summary version of what happens in neurons is that **synapses** cause a small increase or decrease in the voltage; **excitatory synapses** cause an increase, **inhibitory synapses** a decrease. This drives the internal voltage dynamics of the cell, these dynamics are what we will learn about here. If the voltage exceeds a threshold, say  $V_T = -55\text{mV}$  there is a nonlinear cascade which produces a **spike** or **action potential**, a spike in voltage 1-2 ms wide which rises above 0 mV before, in the usual description, falling to a reset value of  $V_R = -65\text{mV}$ , the cell then remains unable to produce another spike for a **refractory period** which may last about 5 ms. We will examine how spikes are formed later, this involves the nonlinear dynamics of ion channels in the membrane; first though we will consider the integrate and fire model which ignores the details of how spikes are produced and simplifies the voltage dynamics.

## The bucket-like equation for neurons

We will now try to extend the bucket-like equation we looked at before so that it applies to neurons. First off we replace  $h$ , the height of the water, by  $V$  the voltage in the cell and  $C$  will be replaced by  $C_m$ , the capacitance of the membrane, the amount of electrical charge that can be stored at the membrane is  $C_m V$ . The amount of electrical charge is the analogue of the volume of water. Thus, voltage is like height, charge is like the amount of water.

The leak is a bit more complicated, because of the chemical gradients, that is the effects of the differing levels of ions inside and outside the cell along and their propensity to diffuse, the voltage at which there is no leaking of charge is not zero, it is  $E_L = -70\text{mV}$ , roughly. This is an important aspect of how neurons behave, and one we will encounter again looking at the



Figure 1: A cartoon to help you remember that there is more sodium outside the cell and more potassium inside.

Hodgkin-Huxley equation: you might at first expect that if the voltage inside the cell was, say, -60 mV then even if there was a high conductivity for potassium at the membrane, the potassium ions would stay in the cell: they are positive ions after all and so a negative voltage means the electrical force is attracting them to the inside of the cell. However, this isn't quite what happens, there is a high concentration of potassium inside the cell and because of the random motion of particles associated with temperature, these have a tendency to diffuse, that is to increase the entropy of the situation by spreading out. It takes a force to counteract this. This is the reversal potential,  $E_L$ , the voltage required for zero current even if there is some conductivity. It turns out that the normal Ohm's law applies around the reversal potential so that the current out of the cell is proportional to  $V - E_L$ .

$G$  is now  $G_m$ , a conductance, measuring the porousness of the membrane to the flow of ions, in other words, it gives the constant of proportionality for the leak current: the leak current out of the cell is  $G_m(V - E_L)$ . We actually divide across by the conductance, and write  $R_m = 1/G_m$ , the resistance. Finally, we write  $\tau_m = C_m/G_m$  to get

$$\tau_m \frac{dV}{dt} = E_L - V + R_m I \quad (5)$$

$I$  might end up being synaptic input, but traditionally we write the equation to match the *in vivo* experiment where  $I$  is an injected current from an electrode, so we write  $I_e$ , 'e' for electrode.  $\tau_m$  is a time constant, using the notation of dimensional analysis we have  $[\tau_m] = T$ . To check this note that the units of capacitance are charge per voltage:  $[C_m] = QV^{-1}$ , the units of resistance is voltage per current  $[R_m] = VI^{-1}$  and current is charge per time,  $[I] = QT^{-1}$  so  $[C_m R_m] = T$ , time.

The equation above leaves out the possibility that there are other non-linear changes in the currents through the membrane as  $V$  changes. This is a problem since there are other non-linear changes in the currents through the membrane as  $V$  changes. The equation above leaves these out, in fact, the nonlinear effects are strongest for values of  $V$  near where a spike is produced, so one approach is to use the linear equation unless  $V$  reaches a threshold value and then add a spike 'by hand'. This has the effect of changing the voltage to a reset value, this mimics what happens in the neuron, or in the Hodgkin Huxley model which we will look at next and which includes the full non-linear dynamics which makes the spike. Anyway, in summary

- $V$  satisfies

$$\tau_m \frac{dV}{dt} = E_L - V + R_m I_e \quad (6)$$

- If  $V \geq V_T$  a spike is recorded and the voltage is set to a reset value  $V_R$ .

The reset value, the voltage after the spike is often set equal to the leak potential. This is the **leaky integrate and fire model**, a surprisingly old model first introduced in [1]. It lacks lots of the details important in the dynamics of neurons, but is useful and often used for modeling the behavior of large neuronal networks or for exploring ideas about neuronal computation in a relatively straight-forward setting.

This model is easy to solve; if  $I_e$  is constant we have already solved it above, up to messing around with constants:

$$V(t) = E_L + R_m I_e + [V(0) - E_L - R_m I_e] e^{-t/\tau_m} \quad (7)$$

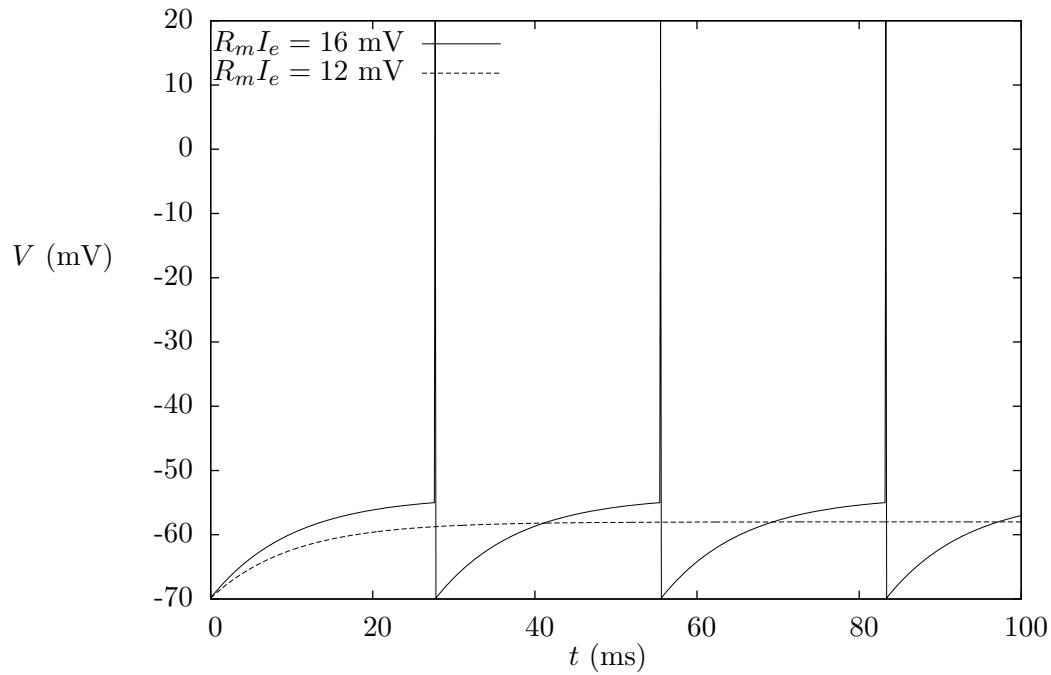


Figure 2: An integrate and fire neuron with different inputs. For  $R_m I = 12\text{mV}$  the voltage relaxes towards the equilibrium value  $V = E_L + R_m I_e = -58\text{ mV}$ . It never reaches the threshold value of  $V_T = -55\text{mV}$ . For  $R_m I = 16\text{ mV}$  the voltage reaches threshold and so there is a spike; the spike is added by hand, in this case by setting  $V$  to  $20\text{ mV}$  for one time step. The voltage is then reset. Here  $\tau_m = 10\text{ ms}$ .

If  $I_e$  is not constant it may still be possible to solve the equation, but in any case the equation can be solved numerically on a computer. An example is given in Fig. 2.

One thing to notice is that there are no spikes for low values of the current. Looking at the equation

$$\tau_m \frac{dV}{dt} = E_L - V + R_m I_e \quad (8)$$

so the equilibrium value for constant  $I_e$ , the value where  $V$  stops changing, is

$$\bar{V} = E_L + R_m I_e \quad (9)$$

Now if this value  $\bar{V} > V_T$  then as the neuron voltage increased towards its equilibrium value,  $\bar{V}$ , it would reach the threshold,  $V_T$ , and spike. Hence, if  $\bar{V} > V_T$  the neuron will spike repeatedly. However if  $\bar{V} < V_T$  then the neuron will not spike for that input because it will never reach threshold.

In fact, we can work out the curve that represents the firing rate as a function of the current; this is called the f-I curve and is shown in Fig. 3. In the model

$$\tau_m \frac{dV}{dt} = E_L - V + R_m I_e \quad (10)$$

which we can solve from our study of odes, it gives

$$V(t) = E_L + R_m I_e + [V(0) - E_L - R_m I_e] e^{-t/\tau_m} \quad (11)$$

so if the neuron has spiked and is reset at time  $t = 0$  and reaches threshold at time  $t = T$ , assume  $V_R = E_L$  we have

$$V_T = E_L + R_m I_e - R_m I_e e^{-T/\tau_m} \quad (12)$$

so

$$e^{-T/\tau_m} = \frac{E_L + R_m I_e - V_T}{R_m I_e} \quad (13)$$

Taking the log of both sides we get

$$T = \tau_m \log \left[ \frac{R_m I_e}{E_L + R_m I_e - V_T} \right] \quad (14)$$

Finally, this is the time between spikes, so the frequency is one over this. It is only defined for  $R_m I_e > V_T - E_L$ , below that there is no spiking and the frequency is zero. The actual gnuplot command used to make the figure was

```
plot [0:22] x>15 ? 1/(.01*log(x/(x-15))) : 0
```

In fact, neurons tend not to have a regular firing rate; they often, for example, show spike rate adaptation. This means that the firing rate decreases even if the incoming current remains constant. As we have seen this isn't modelling in the integrate and fire model, in the integrate and fire model the response to a constant current is a constant firing rate. The model can be extended to include it. For example a slow potassium current could be added, a slow potassium current is a current that would increase every time there is a spike and decrease between spikes. Since a potassium current reduces the voltage inside the cell, it decreases the firing rate; thus, if the cell fires quickly the potassium current increases, decreasing the firing rate until the increase in the potassium when there is a spike balances the decrease between spikes.

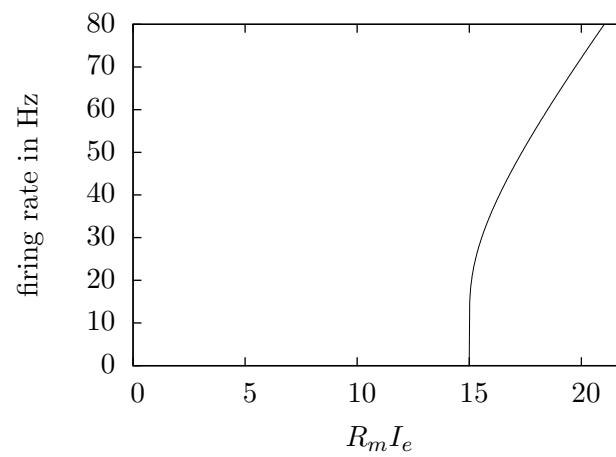


Figure 3: The firing rate, that is spikes per second, for the integrate and fire neuron with different constant inputs with  $\tau_m = 10$  ms,  $V_T = -55$  mV and both the leak and reset given by  $-70$  mV. Notice how there is no firing until a threshold is reached and after that the firing increases very quickly.

## References

- [1] Lapicque, L. (1907). Recherches quantitatives sur l'excitation lectrique des nerfs traite comme une polarisation. J. Physiol. Pathol. Gen, 9:620–635.